Road Accident Detection using MaskRCNNandPrediction usingXgbsoot with Resnet101

KalyaniTiwari[1]and Dr. Sachin Patel[2]
[1]PhD Scholar SAGE University, Indore CSE Department,Indore,India
Email: ktiwari.official@gmail.com
kalyanitiwari@ipsacademy.org
[2]Associate Professor, CSE Department, Sage University, Indore,India
Email: drsachinpatel.sage@gmail.com

Abstract: Inmodern society, road transportation is an essential statutory organ; nevertheless, because of a growth in road accidents, it is responsible for the loss of over a million lives and billions of dollars each year in the worldwide economy. The goal is to offer early warning of prospective accidents so that necessary actions may be taken to limit the frequency and severity of incidents. The system may use multiple data sources to identify and anticipate accidents, such as vehicle speed, braking patterns, road conditions, weather information, and real-time traffic data. If the system detects a probable accident, it may immediately notify emergency services, traffic management authorities, or other relevant parties, allowing them to react more effectively.In the work that has been suggested, detection is carried out using picture frames, and prediction is carried out using metadata. It does this by using a handful of the most recent instance segmentation approaches, such as MaskRCNN for accident detection and Resnet for extracting features from pictures and maps feature to build features for accident prediction models in addition to metadata.In this research, the authors suggested using MaskRCNN for detecting and predicting road accidents by combining Xgbsoot with Resnet101. Both our prediction and detection accuracy comes in at 97.67%. Our prediction accuracy is 93.87%.

Keywords: Road Accident, Detection, Prediction, MaskRCNN, Xgbsoot, Resnet101.

I. INTRODUCTION

Traffic accidents are a major contributor to personal injury, wrongful death, and economic devastation on a global scale. Over 1.35 million people are killed on the world's roads each year, and many more are injured or rendered unable to work as a direct result of these collisions, as reported by the World Health Organization (WHO). These incidents can result in large economic losses for various reasons, including damage to property, medical expenses, and missed time at work [1].

New technology is needed to identify and anticipate accidents in real-time or in advance to reduce the overall number of accidents and the damage they cause [2]. Road Accident Detection and Prediction is a system that employs technology, such as sensors, cameras, and machine learning algorithms, to detect possible accidents and send early warnings to drivers and authorities. This system is called RADAR (Road Accident Detection and Reconstruction) [3].

The system can gather data on various characteristics, such as vehicle speed, braking patterns, weather conditions, and road conditions, and then analyze this data using algorithms to identify and anticipate accidents. The system may notify drivers and authorities of an accident, giving them information about its location, severity, and potential causes [4]. This information may assist the authorities in taking the necessary actions, such as rerouting traffic flow, dispatching emergency services, or warning motorists.

Systems that can detect and predict road accidents have the potential to save lives, decrease the number of people injured, and reduce the amount of money lost as a result of road accidents. The technology can also offer drivers real-time traffic updates, assisting drivers in avoiding probable accident hotspots and enhancing the flow of traffic overall. Because of this, the implementation of technologies that can detect and predict road accidents may considerably increase the safety of roadways and lessen the severity of the effects of collisions.

The purpose of detecting and predicting road accidents is to make roads safer and cut down on the number of accidents, as well as the number of injuries and deaths that are caused by traffic collisions. When accidents are detected and predicted in real-time, it is feasible to take prompt action to reduce the associated risks, such as rerouting traffic, stopping roads, or calling emergency services.

The contribution of work is below point to point.

Existing work:

- Detection with semantic segmentation.
- Prediction using begging methods.
- Prediction suffers from overfitting.
- Due to the division of frames for semantic segmentation, a few elements from frames are missed.

Proposed:

- Detection uses instance segmentation.
- Prediction using boosting method, which is robust.
- Parallel modelling is reliable against overfitting.
- Instance segmentation treats each entity as a single instance, reducing the number of framed skipped and producing better results.

The other parts of the investigation were carried out in the following manner: Existing research on the classification of road accidents using a machine learning technique is reviewed in Section 2. In Section 3, we introduce a novel algorithm called MaskRCNN. It combines Xgbsoot with Resnet101 to identify and forecast road accidents. The summary of the experiment, evaluation, and discussion, as well as the results, can be found in Section 4. The conclusion can be found in Section 5.

II. LITERATURE REVIEW

Image categorization is one of the most fundamental challenges in computer vision. In a nutshell, image categorization involves assigning a label to a picture. The number of photographs and target classes will determine this activity's difficulty. CNNs, the core of current CVs based on deep learning, were developed to solve this challenge (DL). Its significance may be explained by the fact that it is so successful in lowering the total number of model parameters while maintaining their high level of accuracy. As a result, the implementation of CNN as it is now practised was suggested [7]. The findings of these early models were crucial in developing more sophisticated convolutional neural networks. Because of advancements in image processing, computer vision-based accident detection has developed throughout the years. Before deep learning, I worked on a system that analyzes photos captured by roadside surveillance cameras to identify damaged automobiles. The system that has been suggested makes use of five Support Vector Machines (SVMs) that have been trained using gradient histograms and grey-level co-occurrence matrix resources.

The approach of Spatial-Temporal Convolutional Learning (STCL) was proposed by Z. Liu and colleagues in 2022. This approach makes use of unidirectional convolution inside a targeted temporal block to efficiently capture periodic dependencies across very short time scales. The extraction of interaction dependencies and the reduction of feature dimensions are the purviews of a spatial-temporal fusion module. We also use location encoding to identify anomalies in intricate traffic conditions since the types of accidents often directly impact the level of congestion in the area. Numerous real-world experiments have confirmed our suggested method's efficacy [5].

Angus G. Perera, and others, 2022. In the face of difficult driving conditions, this approach resulted in mistakes and misclassifications. We propose combining camera configuration data with a neural network detector to construct a distance versus pixel model for accurate road severity distance computation. The precision of distance calculations will improve as a result of this. We use the camera's data to transform the deep neural network's expected 2D picture data into a 3D environment. The updated model was tested using data collected in the real world. The newly created combination model improved accuracy over the lane-line technique by 36% for the right-hand side distance and by 37.5% for the left-hand side distance [6].

2021 F. Sajid et al. We developed five distinct iterations of the Efficientdet model (Efficientdet (D0-D4)) for the detection aim and compared the best to Faster R-CNN and Yolo-V3. With the parameters learning rate of le3, 50 epoch, batch size of 4, and step size of 250, EfficientDet-D3 detects distracted drivers with a MAP of 99.16%, making it the most accurate model. Just because you're a responsible driver doesn't mean you have to be reckless. The experimental findings demonstrate the superiority of the suggested technique over its predecessors.

To cite: L. Canzian et al. 2016. To make precise local predictions, we need an online learning technique that considers this data and adjusts the relative importance of each sensor. Using the feasible scenario, we estimate our system's worst-case misdetection and false alarm probability. As a result, the sensors can tell the difference between crashes and other traffic behaviours thanks to the presence of unknown weights. Our analysis, based on data collected from the 405 motorway in Los Angeles County, demonstrates that the suggested strategy is effective [8].

Authors: Fang, J., et al., 2022. The contributions may be divided into three categories. 1) To aid the driver in attention prediction, we provide the components of the semantic context of the visuals and verify the manifest-promoting influence. A graph convolution network (GCN) is used for the semantic images to convey the qualities of the semantic context being shown. 2) We merge the characteristics of the RGB frames with the features of the semantic images using a careful method. The information is then transferred between frames via a convolutional LSTM module. Thirdly, particulars of all kinds are compiled [9].

Zhou, Y.-F., et al., 2021.The generator may participate in gradient penalty-compliant joint learning with ground-truth pictures and discriminators with this design. The deeper convolutional neural network may greatly improve the image's overall quality by fusing any residual properties. One option is to combine the remaining characteristics. Several unique deep convolutional neural network models were used on diverse datasets to assess the strategy's performance. Out of all of these models, the one that performed the best was a prediction model built on top of the VGG network. The structural similarity index was 0.921, and the peak signal-to-noise ratio was 32.67. Therefore, both metrics were quite strong. We then use the tracking model to create a risk score assessment strategy predicated on the target's position. It can send out alerts 1.95 ms faster than before under ideal conditions. This is because it relies on the location of the target. Based on these findings, we can say with some certainty that our method has the potential to reduce the occurrence of automobile collisions [10].

2009, M. Althoff et al. Measurement errors and the likely behaviour of other road users are included into the projection. Furthermore, the road's shape, which limits the driver's range of motion, and the interactions between the different traffic participants are all considered. The result of using the approach outlined here would be an estimate of how likely an accident would be along a certain route for an autonomous car. The time-consuming computations are performed offline, making for a simplified online approach suitable for real-time software. Because of this, the method described here works [11].

2022 L. Jiang et al. To foresee when a motorist would engage in potentially dangerous manoeuvres while driving, an LSTM-based model is used. Output from inattention detection mixed with POI and temperature data suggests these aberrant activities may lead to risky driving circumstances such as rapid acceleration/deceleration, aggressive lane changing, etc. The model is used to foresee potentially dangerous driving behaviours (related to distraction). This model's foundation is derived from a combination of POI and weather data with the results of inattention detection. We gathered over 120,00 actual driving traces from over 200 people to assess the efficacy of our proposed solution. Test findings show that our algorithm achieves WAs of 92.27 percent for detecting drowsy driving and 91.67 percent for foreseeing erratic driving. The numbers above are based on information gleaned from the trials. These findings reveal the great promise of the paradigm in promoting safe driving practices and reducing traffic fatalities [12].

R. Quan and colleagues 2021 recommend using a gated shifting operation to get additional knowledge about the flow of individuals. Whether or not a pedestrian is planning to cross the street will significantly influence where they should position themselves spatially. The global dynamics of the scene and information on the intents of pedestrians aremodelled to accomplish this goal's desired spatial alterations. Finally, we reweight the output channels dynamically depending on how the scaling of vehicle speed impacts them and include the speed variations into the output gate. Because of the vehicle's motion, the proportions of the bounding box projected for the pedestrian would vary; more precisely, the bounding box would expand as the vehicle drew closer to the pedestrian. During the rescaling process, we consider the relative movement, and we alter the size of the bounding boxes for pedestrians in a manner that is proportional to this movement. Our performance was measured against three distinct pedestrian trajectory forecasting standards, and the results showed that we obtained performance at the forefront of the industry [13].

By considering the possibility of a collision with automobiles in the adjacent lanes, the strategy described by H. Woo et al. in 2017 reduces the incidence of false alerts. Lane-change detection data is considered, and trajectory prediction is used whenever the target vehicle attempts to change lanes. Using a traffic dataset of over 500 lane changes, we showed that the suggested approach could significantly improve detection performance [14]. Because of this, we could judge for ourselves how well the technique worked.

N. Lyu et al. 2022 developed a collision warning model for use in a V2V setting using the suggested comprehensive prediction model for lane-change behaviour, the driving trajectory prediction model, and the oriented bounding box (OBB) detection technique. This model was developed with vehicle-to-vehicle communication in mind. Finally, a cut-in experiment was built and conducted in a multi-vehicle setting using a driving simulation platform and an automobile experiment in the real world. The suggested cut-in collision warning model was superior to the conventional collision warning model by comparing the warning confusion matrix with the warning time. Future optimization of ADAS performance in cut-in conditions may be achieved with the help of the novel modelling concepts and theoretical framework suggested by this research [15].

To address this challenge, S. Atev et al. 2005 offer a vision-based system and detail the enhancements required to attain real-time performance. Several state-of-the-art algorithms, including one that use time as an axis to forecast low-overhead accidents, are presented in this article. The suggested system is capable of real-time operation on films with a resolution of quarter-video graphics array (VGA) (320x240), notwithstanding the inherent unpredictability of external variables. Errors in estimating the target's location and size in a test video sequence are shown and quantified, along with some experimental data [16].

2022 T. Huang et al. TDFoA prediction was built using a deep 3D residual network (D3DRN-AMED) to tackle these issues. We know that you're smart. Therefore, we know you're paying attention. Convolution LSTM is used to build this network on consecutive frames, and successive frames are used to eliminate the impact of transient looks. When considering the wide variety of driving scenarios, the convolution LSTM can finish the feature transfer across frames. The D3DRN-AMED has a soft-threshold-based attention mechanism as one of its nonlinear transformation layers. This has been done to get rid of the features associated with the noise. An encoding and decoding module has been included to facilitate the extraction of multi-scale properties further. Then, if there is a large disparity between DFoA and TDFoA, it is proposed that a neural network-based technique be employed to ascertain whether or not the driver is paying attention. This approach may allow for reliable detection of driver attention without requiring the determination of a threshold. Several studies have shown that easily distracted drivers are more likely to have an accident.

III. PROPOSED WORK

To enable automobiles to move more smartly, ADAS-like technologies play a crucial role which makes the driving experience with pleasure and adding a layer of safety into drivers' lives; these technologies are in the developing or progressing phase where there is a huge scope of adding more safety, security and decisions into automotive vehicles control units, this creates a space for Artificial Intelligence to makes it smarter and safer, proposed work also adds improvements in it, proposed work presents road accident detection and prediction using deep learning branch of Artificial Intelligence.

The proposed work performs detection based on image frames and prediction based on metadata. It uses a few latest instance segmentation methodologies, such as MaskRCNN for accident detection and Resnet to extract features from images and maps feature to create features for accident prediction models with additional metadata.

3.1 Basic overview flow of proposed work

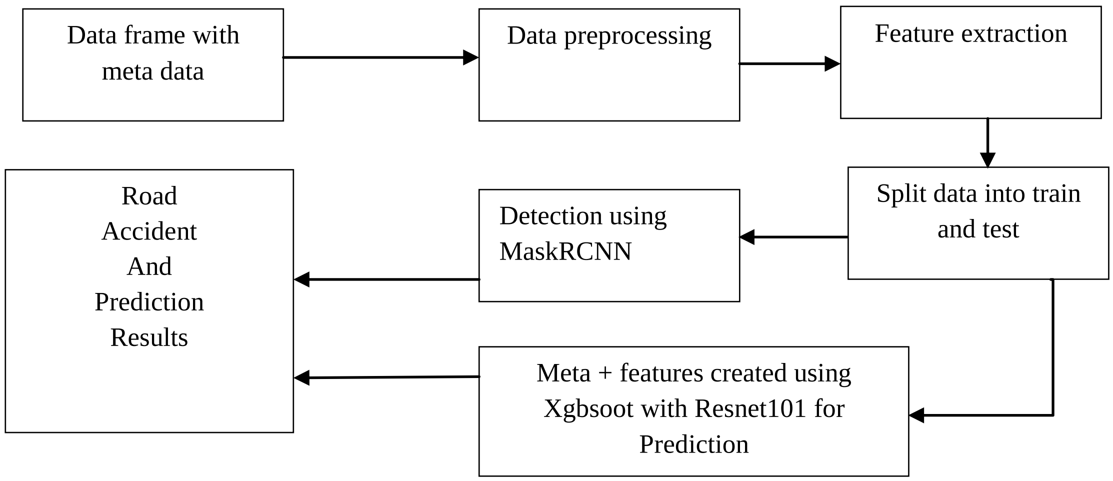

Figure 1: Basic overview flow of proposed work.

Figure 1 shows the high-level architecture of the proposed system, which begins with loading data which is then processed and makes it ready for feature extraction, then data splitting is performed for train and testing, also segmenting the metadata with images, which is used by prediction and detection model to return results.

3.2 Proposed algorithm

3.2.1 Algorithm for Split Dataset and Extract Meta Data

Algorithm 1: To Split Dataset and Extract Meta Data

Input: Dataset D, Annotation file f
Output: Train, Test

```
L={'file_name':,'features':[]}
N,Count=0
Load D & f
For each I in D:
        N++
          For each j in f:
          If L[j][' file_name']==I
              L[j]['features']=f[j]
          count++
                If count<=N-1/2:
          Df=L.to_dataframe()
          Df.to_csv('./Train/mt.csv')
          Move(D,'./Train')
                If count>N-1/2:
          Df=L.to_dataframe()
          Df.to_csv('./Test/mte.csv'')
```

```
Move(D,'./Test')
  If count==N:
   Return 0
```

Algorithm 1 is about data splitting and creating csv of metadata, which helps predict as it begins with taking the dataset and annotations file and iterating over it. Iteratively it matches the name of Files from Json and moves files into the train and test folder based on the number of counts of files; it also separates the JSON based on the file name and stores it in CSV with Mt.csv for train and mte.csv for a test. When counter variable N becomes the size of several files in a folder, it exits with 0.

3.2.2 Algorithm for Prediction and Detection

Algorithm 2 – Prediction and Detection

Input: Train
Output: Detection and Prediction

```
os.listdir(./Train)
Load D
Read mt.csv store it into mt
for each columns i in mt:
ifmt[i].mean>=1.2*mt[i].median:
dropmt[i]
else
continue
x, y=mt[:,-1],mt[:-1]
loadXGboost
      //set parameters
      // pass x,y into XGboost model and save model in M
       //Load mte.csv in mte
x, y=mte[:,-1],mte[:-1]
M.preditct(x)
       Return M.predict_proba(x)
       For each image i in D:
        Load i
       //pass into ResNet101 to extract features matrix F
      //extract region of interest from F
      //apply region proposal network gives intersection over union (IOU)
if IOU>=0.75
create mask M
else
continue
return 0
```

Algorithm 2 is used for the prediction and detection of a road accident. Initially,thealgorithm list files in the training data folder and then read data and their respective json, which gives information like class, on historical data, and regions affected in the last algorithm count Regions and area affected is also added to it, which is utilized here; once reading of files completed, outliers were removed from the working data then, features were assigned to x and target to y, then model loaded and features variables passed into model then predicted probability returned by the algorithm in case of prediction, and for detection, images are iterated,then features extraction using ResNet101 on results of its regions of interest are extracted for region proposal network, after that intersection over union is identified after that, if IOU is greater than 75% then we keep it for masking and if not then remained unmasked and move ahead, once all files visited algorithm Terminates with exit 0.

3.3 Model Arch:

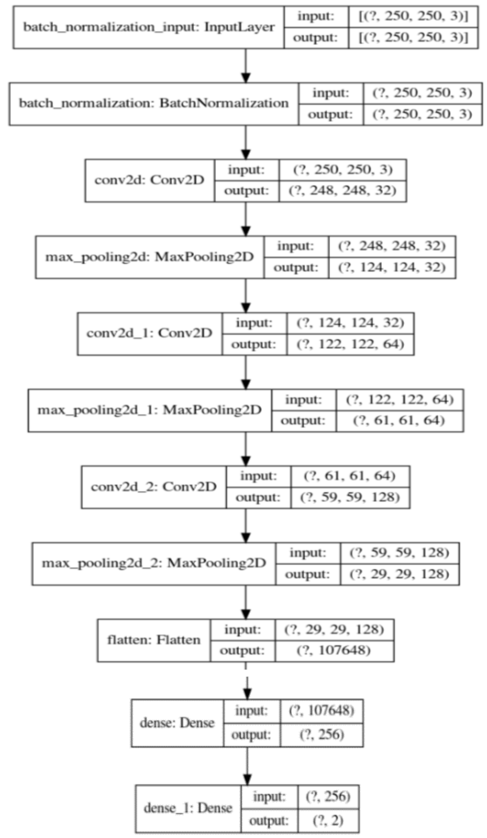

Figure 2: Proposed model Architecture.

Figure 2 shows the layered model architecture; it was observed from the architecture that the model contains 3 Con2D layers and one layered in between two Max_pooling layers which makes the model stand while applying filtering methods and to avoid overfitting during two dense layers appended into a network which makes detection model architecture reliable against high variance.

IV . IMPLEMENTATION AND RESULT

4.1 Hardware and software required

The Hardware and software required for Road Accident Detection and Prediction may vary depending on the specific implementation and requirements of the system. Here are some hardware and software components used for this purpose:

4.1.1 Hardware:

a) Cameras or sensors capture real-time data on traffic and road conditions.
b) GPS devices to track the location of vehicles.

c) Computing hardware, such as servers or cloud infrastructure, to process and analyze data in realtime.
d) Communication devices, such as radios or cellular modems, send alerts and notifications.

4.1.2 software:

a) Data collection and management software to collect and store data from various sources.
b) Data analysis and processing software, such as machine learning algorithms or statistical models, to identify patterns and predict accidents.
c) Alert and notification software to notify authorities and drivers of potential accidents.
d) Visualization software to provide real-time traffic updates and display accident information to drivers and authorities.

4.1.3 Python Libraries:

a) OpenCV for computer vision and image processing.
b) TensorFlow or PyTorch for machine learning and deep learning.
c) NumPy and Pandas for data processing and analysis.
d) Scikit-learn for predictive modelling and statistical analysis.
e) Flask or Django for web development and creating APIs.

4.2 Dataset

Link: https://www.kaggle.com/datasets/ckay16/accident-detection-from-cctv-footage

The dataset contains three directories train, Val and tests. Each directory contains CCTV footage of road accidents, the dataset is taken from YouTube, clips of various road accident videosareclipped, and a repository is created from those. This dataset is available on Kaggle to train and test road accident detection and prediction models. It contains around 1K clips and approximately 20 frames per clip are used for training the accident detection and prediction models.

4.3 Illustrative Result

Figure 3 shows the results of accident prediction on different image frames, with labels as an actual and predicted class; it was observed from the results that model performs fairly better, even on different viewing angles from camera frames and returns whether a particular timeline of camera footage records accident or not.

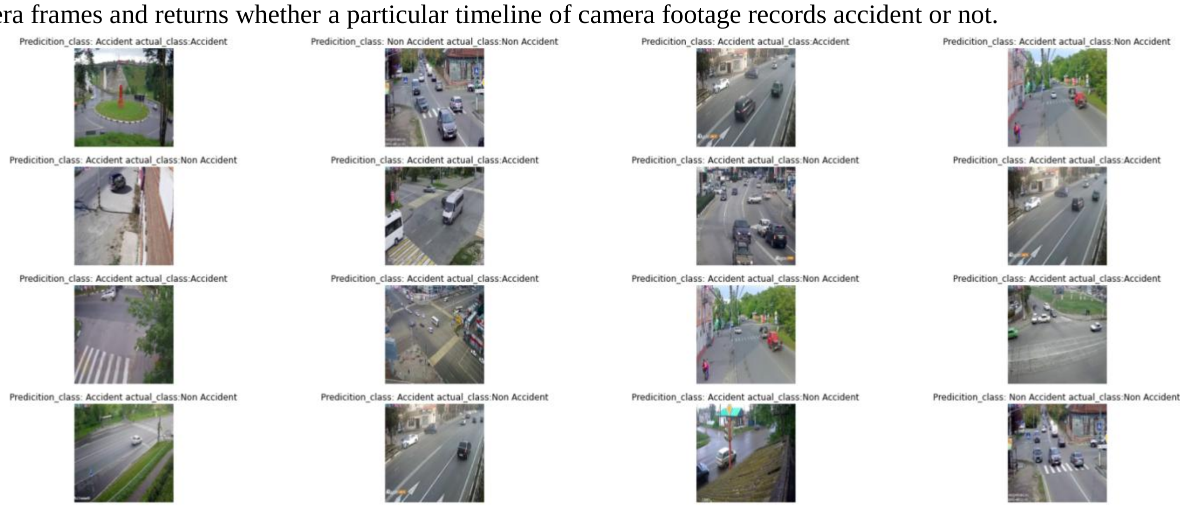

Figure 3: shows the results of accident prediction on different image frames, with labels as an actual and predicted class.

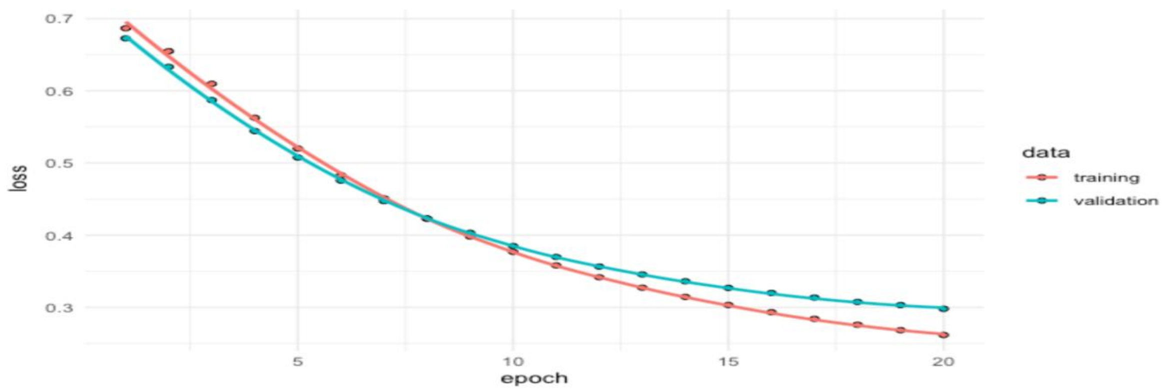

Figure 4: Shows loss curves based on different values of epochs for detection models.

Figure 4 shows loss curves based on different values of epochs for detection models, it was observed from the curve that initially, loss values are at peak, and as the model starts moving towards higher epoch number sides, loss values start to decline, and after a certain point of epoch values is start becoming a constant movement in loss values.

4.4 Model performance on prediction:

Table 1.Model performance on prediction.

Classifiers	Accuracy
SimpleCart [19]	70.81%
MLP [20]	62.48%
ID3 [21]	80.21%
KNN[22]	87.33%
JR8 [23]	78.02%
Proposed Xgbsoot with Resnet101	93.87%

Table 1 and Figure 5 compare the prediction performance of the proposed model with existing solutions, specifically with corresponding classifiers used in classification by existing solutions. It was observed from the table that tree-based models without ensemble performs better than the perception layer, which allowsalayered network for classification, but distance-based algorithms outperform due to robust overfitting processing, an ensemble with error handling, which is used in the proposed surpasses all existing solutions makes it the best performer in terms of prediction from the metadata of accident history of a particular area.

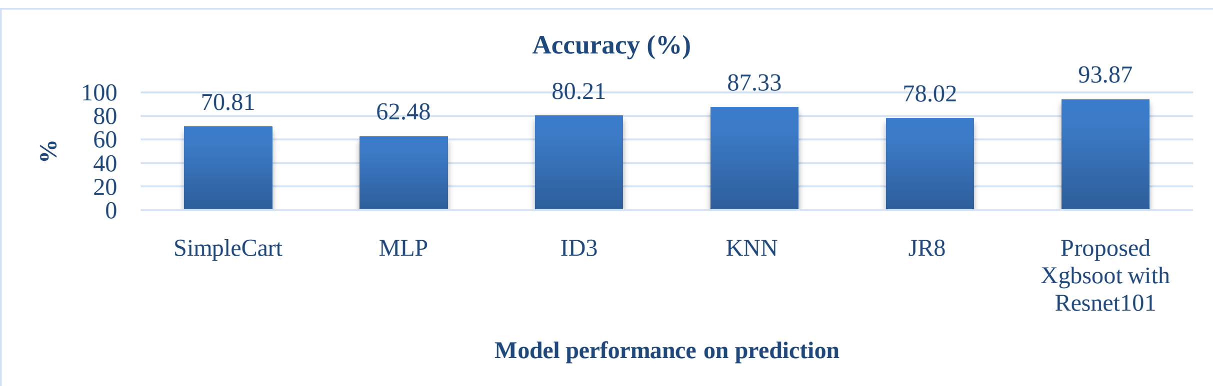

Figure 5: Model performance on prediction

Table 2- For Detection

Model	Accuracy (%)
IoT based Devices [24]	86.4
Decision Tree Algorithm [25]	90.23
Proposed MaskRCNN	**97.67**

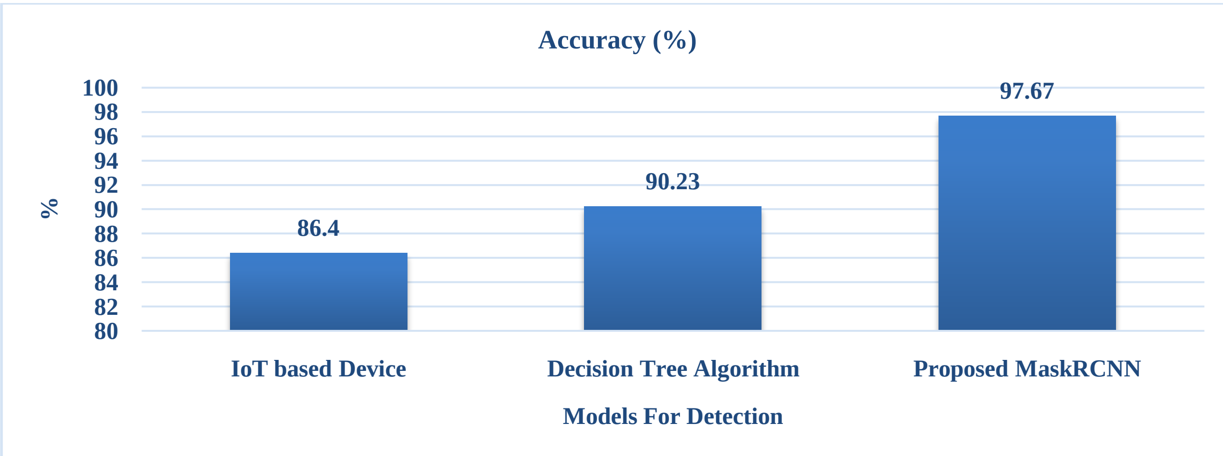

Figure 6: For Detection

Table2 and Figure 6 show a comparative analysis of the detection task with solutions that use image analyses to detect accident scenarios in video footage; it was observed from the table that the proposed instance segmentation model surpasses models with semantic segmentation those not able to segregate each frame element from the clips. Still, instance based to create a separate instance for each object in the image frame.

V. CONCLUSION

The term "road accident detection and prediction" refers to using technological means, such as sensors, cameras, and machine learning algorithms, to identify and anticipate traffic mishaps in realtime or the future. The goal is to forewarn prospective mishaps so that preventative actions may be taken to lessen the frequency and severity of accidents. Vehicle speeds, braking habits, road conditions, weather reports, and live traffic data are only some of the data that the system may use to identify and prevent accidents. If an accident is suspected, the system may immediately contact the appropriate authorities, such as those in charge of traffic control or emergency services. This would allow for faster action to be taken. Using Xgbsoot and Resnet101, the authors of this research suggest employing MaskRCNN to identify and forecast traffic accidents. Our results show a prediction accuracy of 93.87 percent and a detection accuracy of 97.67 percent.

References

[1] Yassin, S.S., Pooja Road accident prediction and model interpretation using a hybrid K-means and random forest algorithm approach. SN Appl. Sci. 2, 1576 (2020).

[2] U. Alvi, M. A. K. Khattak, B. Shabir, A. W. Malik and S. R. Muhammad, "A Comprehensive Study on IoT Based Accident Detection Systems for Smart Vehicles," in IEEE Access, vol. 8, pp. 122480-122497, 2020, doi: 10.1109/ACCESS.2020.3006887.

[3] J. Fang, J. Qiao, J. Bai, H. Yu and J. Xue, "Traffic Accident Detection via Self-Supervised Consistency Learning in Driving Scenarios," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 7, pp. 9601-9614, July 2022, doi: 10.1109/TITS.2022.3157254.

[4] Weiming Hu, Xuejuan Xiao, D. Xie, Tieniu Tan and S. Maybank, "Traffic accident prediction using 3-D model-based vehicle tracking," in IEEE Transactions on Vehicular Technology, vol. 53, no. 3, pp. 677-

694, May 2004, doi: 10.1109/TVT.2004.825772.
[5] Z. Liu, R. Zhang, C. Wang, Z. Xiao and H. Jiang, "Spatial-Temporal Conv-Sequence Learning With Accident Encoding for Traffic Flow Prediction," in IEEE Transactions on Network Science and Engineering, vol. 9, no. 3, pp. 1765-1775, 1 May-June 2022, doi: 10.1109/TNSE.2022.3152983.
[6] A. G. Perera and B. Verma, "Road Severity Distance Calculation Technique Using Deep Learning Predictions in 3-D Space," in IEEE Access, vol. 10, pp. 68000-68008, 2022, doi: 10.1109/ACCESS.2022.3185997.
[7] F. Sajid, A. R. Javed, A. Basharat, N. Kryvinska, A. Afzal and M. Rizwan, "An Efficient Deep Learning Framework for Distracted Driver Detection," in IEEE Access, vol. 9, pp. 169270-169280, 2021, doi: 10.1109/ACCESS.2021.3138137.
[8] L. Canzian, U. Demiryurek and M. v. der Schaar, "Collision Detection by Networked Sensors," in IEEE Transactions on Signal and Information Processing over Networks, vol. 2, no. 1, pp. 1-15, March 2016, doi: 10.1109/TSIPN.2015.2504721.
[9] J. Fang, D. Yan, J. Qiao, J. Xue and H. Yu, "DADA: Driver Attention Prediction in Driving Accident Scenarios," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 6, pp. 4959-4971, June 2022, doi: 10.1109/TITS.2020.3044678.
[10] Y. -F. Zhou, K. Xie, X. -Y. Zhang, C. Wen and J. -B. He, "Efficient Traffic Accident Warning Based on Unsupervised Prediction Framework," in IEEE Access, vol. 9, pp. 69100-69113, 2021, doi: 10.1109/ACCESS.2021.3077120.
[11] M. Althoff, O. Stursberg and M. Buss, "Model-Based Probabilistic Collision Detection in Autonomous Driving," in IEEE Transactions on Intelligent Transportation Systems, vol. 10, no. 2, pp. 299-310, June 2009, doi: 10.1109/TITS.2009.2018966.
[12] L. Jiang, W. Xie, D. Zhang and T. Gu, "Smart Diagnosis: Deep Learning Boosted Driver Inattention Detection and Abnormal Driving Prediction," in IEEE Internet of Things Journal, vol. 9, no. 6, pp. 4076-4089, 15 March15, 2022, doi: 10.1109/JIOT.2021.3103852.
[13] R. Quan, L. Zhu, Y. Wu and Y. Yang, "Holistic LSTM for Pedestrian Trajectory Prediction," in IEEE Transactions on Image Processing, vol. 30, pp. 3229-3239, 2021, doi: 10.1109/TIP.2021.3058599.
[14] H. Woo et al., "Lane-Change Detection Based on Vehicle-Trajectory Prediction," in IEEE Robotics and Automation Letters, vol. 2, no. 2, pp. 1109-1116, April 2017, doi: 10.1109/LRA.2017.2660543.
[15] N. Lyu, J. Wen, Z. Duan and C. Wu, "Vehicle Trajectory Prediction and Cut-In Collision Warning Model in a Connected Vehicle Environment," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 2, pp. 966-981, Feb. 2022, doi: 10.1109/TITS.2020.3019050.
[16] S. Atev, H. Arumugam, O. Masoud, R. Janardan and N. P. Papanikolopoulos, "A vision-based approach to collision prediction at traffic intersections," in IEEE Transactions on Intelligent Transportation Systems, vol. 6, no. 4, pp. 416-423, Dec. 2005, doi: 10.1109/TITS.2005.858786.
[17] T. Huang and R. Fu, "Driver Distraction Detection Based on the True Driver's Focus of Attention," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 10, pp. 19374-19386, Oct. 2022, doi: 10.1109/TITS.2022.3166208.
[18] https://www.kaggle.com/datasets/ckay16/accident-detection-from-cctv-footage
[19] Wahab L, Jiang H (2019) Severity prediction of motorcycle crashes with machine learning methods. Int J Crashworthiness 24:1–8
[20] Sameen MI, Pradhan B (2017) Severity prediction of trafc accidents with recurrent neural networks. ApplSci 7(
[21] Fentahun A (2011) Mining road trafc accident data for predicting accident severity to improve public health-role of driver and road factors in the case of Addis Ababa. PhD thesis, Addis Ababa University
[22] Xiao J (2019) SVM and KNN ensemble learning for trafc incident detection. Phys A 517:29–35
[23] Castro Y, Kim YJ (2016) Data mining on road safety: factor assessment on vehicle accidents using classifcation models. Int J Crashworthiness 21(2):104–111
[24] Dashora, C.; Sudhagar, P.E.; Marietta, J. IoT based framework for the detection of vehicle accident. Clust. Comput. 2020, 23, 1235–1250.
[25] Sani, H.M.; Lei, C.; Neagu, D. Computational complexity analysis of decision tree algorithms. In International Conference on Innovative Techniques and Applications of Artificial Intelligence; Springer: Berlin, Germany, 2018; pp. 191–197.